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Optimized reactive power management system for smart grid architecture

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ABSTRACT

The Indian power grid is an extensive and mature power system that transfers large amounts of electricity between two regions linked by a power corridor. The increased reliance on decentralized renewable energy sources (RESs), such as solar power, has led to power system instability and voltage variations. Power quality and dependability in a smart grid (SG) setting can be enhanced by the careful tracking and administration of solar energy generated by panels. This study proposes a number of reactive power regulation algorithms that take smart grids into account. When developing a kernel, debugging is a must in optimal reactive power management. In this research, a debugging primitive called physical memory protection (PMP), a security feature, is considered. Debugging in the kernel domain requires specialized tools, in contrast to the user space where we have kernel assistance. This research proposes an optimal reactive power management in smart grid using kernel debugging model (ORPM-SG-KDM) for managing the reactive power efficiently. This research achieved 98.5% accuracy in kernel debugging and 99.2% accuracy in optimal reactive power management. Kernel debugging accuracy is increased by 1.8% and 3% of reactive power management accuracy is increased.

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1. INTRODUCTION

The conventional perception about power and energy systems is shifting from centralized to decentralized models [1]. Driven by demand-side management, transactive energy, and demand response, smart grids enable the integration of dispersed energy resources and encourage inclusive management engaging end-users [2]. Since all decisions are not made in one central location in this new smart grid paradigm, ensuring the reliability and quality of the grid's service becomes more challenging. Electrical and computer engineers must work together for smart grid implementation to be a success [3]. To lay the groundwork for sufficient methods of monitoring, controlling, managing, and operating, electrical engineers must guarantee the correct physical operation of the smart grids and their components. When it comes to managing and operating the smart grid and its components, computer engineers are crucial in supplying the correct computational models and tools, which in turn accurately reflect all the many stakeholders [4]. These models need to take into account the unique and shared objectives of each player to lay the groundwork for cooperative and competitive interactions that can fulfill everyone's needs while also ensuring the system's long-term viability from a technical, environmental, and economic perspective [5].

Everyone from major corporations to individual households may play an active role in smart grids with its distributed architecture, which allows, incentivizes, and greatly benefits end-user participation [6].

The fluctuation of energy demand, which frequently more than doubles during on-peak hours compared to off-peak demand, is one of the primary concerns in the development and operation of electric networks [7]. In the past, this variance would lead to the building of power plants and substantial investments in network connections and substations. The generating side becomes more volatile due to the widespread use of renewable energy sources, making it more difficult to achieve a balance between generation and consumption [8]. Flexibility on the demand side, ease of system operation, and ability to deal with growing percentage of renewable energy can be achieved by smart grid players' active participation made possible by transactive energy and demand response [9]. Within the framework of smart grids, smaller grids called microgrids can be constructed and managed. Those grids are operated and managed at the local level and are geographically limited [10]. They can be thought of as limited geographic regions where the power grid is typically linked to the main grid but can also function independently in island mode [11].

For power systems to function at peak efficiency, reactive power regulation is an essential component. Recent global blackouts and voltage collapses have inadequate reactive power as one of their main causes [12]. Finding the best possible values for controllable variables in order to minimize an objective function is the general goal of reactive power control schemes [13]. Reactive power regulation poses a number of challenging restrictions and is hence a nonlinear optimization issue from a computational standpoint [14]. Reducing active power losses, minimizing voltage deviations, and improving the voltage stability margin are the primary objectives of the reactive power control problem that have been discussed in the literature [15]. The active and reactive power management is shown in Figure 1.

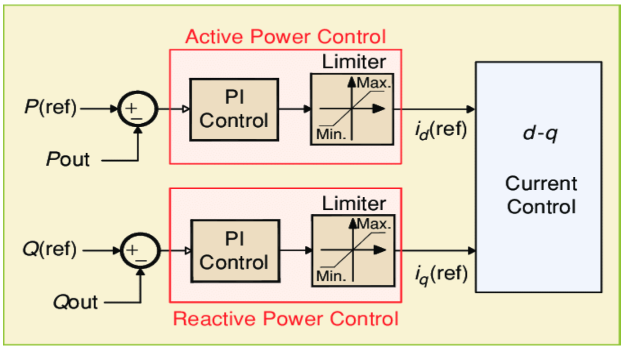

Figure 1. Active and reactive power management model

The proposed model uses kernel debugging for optimal reactive power management in smart grid. To make debugging and kernel development easier, certain operating system kernels include a debugger called a kernel debugger. When the kernel debugger is launched, all system operations come to a standstill in the SG. Unless it is exited, hardware interrupts will not be enabled and no thread will be able to make progress on any CPU [16]. So, one can take their time studying a static image of the entire system in kernel debugging land (KDL).

Optimal reactive power management (ORPM) shows up as a difficult nonlinear issue in power system engineering. Reduced losses, better voltage profiles, and increased power system efficiency are the goals of ORPM. A more responsive and adaptive control strategy that can adapt to different load conditions and system configurations is made possible by this approach, which goes beyond traditional rule-based methods [17]. Engineers designing power systems can lessen the likelihood of outages and broken machinery by shifting reactive power generation [18]. ORPM is a set of procedures and methods for improving power system control, monitoring, and compensation. Capacitors, reactors and synchronous condensers are examples of reactive power control equipment that could be utilized in ORPM techniques [19]. To control voltage levels and offset variations in reactive power demand, these devices can inject or absorb reactive power as required [20]. This research proposes an optimal reactive power management in smart grid using kernel debugging model (ORPM-SG-KDM) for managing the reactive power efficiently.

2. LITERATURE SURVEY

It is usual practice to link distributed energy resources (DERs). to the grid via inverters, which are dc/ac converters. As a result, inverters are being more integrated into distribution systems alongside DERs. Revisions to grid requirement criteria for DERs are made based on their level of development and penetration. Ancillary reactive power service can be provided by DERs through the regulation of their output reactive power, with the new grid codes. The key contribution of this paper designed by Safavizadeh *et al*. [1] is a practical procedure for reactive power management of inverter-based DERs (IBDER). Home energy management (HEM) systems play a crucial role in enhancing consumers' economic benefits due to the increasing use of distributed energy resources, energy storage systems (ESS), and electric vehicles (EVs) on a domestic scale. In the past, these systems focused on reducing active power use while ignoring reactive power. The power factor at the home-to-grid interface can be negatively affected by a large imbalance between reactive and active power. In order to maximize the power factor and guarantee that HEM systems achieve operational and budgetary objectives, Aldahmashi *et al*. [2] offered a novel approach to optimizing their performance. This method is based on precisely calculating the active and reactive power values for both electric vehicles and energy storage systems, as well as carefully controlling the thermostatic load according to user preferences.

Research into networked microgrids (NMGs) resilient reactive power scheduling under harsh environments is the focus of this work performed by Shaker *et al*. [3]. A two-stage paradigm is suggested, with the first stage utilizing here-and-now (HAN) judgments and the second stage utilizing wait-and-see (WAS) decisions. The whole problem is expressed in mixed-integer linear programming, which is the stochastic programming approach that connects the HAN and WAS stages. As electricity distribution networks transition from passive to active systems, operators face new issues related to efficiency and reliability. Tziovani *et al*. [4] proposed a system for controlling and managing energy in an active distribution grid that includes prosumers. The author developed a multi-objective optimization model that ensures safe and dependable grid operation while minimizing the cost of power for prosumers and the cost of grid energy losses. This is accomplished by finding the active and reactive power set-points of the grid-integrated photovoltaic (PV) and storage systems. Because the resulting optimization model is not convex, a convex second-order cone program that produces. The kernel debugging uses in different aspects is represented in Table 1.

Table 1. Kernel debugging uses in different aspects

Aspect	Existing Works	Proposed Model
Optimization approach	Mostly rule-based or traditional machine learning techniques with limited adaptability.	Uses kernel debugging for real-time diagnostics and adaptive optimization.
Fault detection and debugging	Relies on surface-level fault detection; lacks deep system diagnostics.	Kernel debugging enables real-time fault diagnosis at the system level.
Cybersecurity measures	Focuses on encryption and network security but lacks low-level intrusion detection.	Monitors system processes for anomalies, preventing cyber threats proactively.
Scalability	Limited scalability in large-scale smart grids with increased DERs.	Supports distributed control and edge computing for scalable operations.
Real-time response	Slower response due to reliance on centralized processing.	Faster real-time decision-making through optimized data handling.
Interoperability	Compatibility issues due to lack of standardized communication frameworks.	Ensures seamless integration with existing and emerging smart grid systems.
Computational efficiency	High computational overhead due to centralized processing and lack of low-level optimization.	Uses kernel-level diagnostics to optimize system resource allocation.

3. PROPOSED MODEL

To improve grid stability and efficiency, the reviewed literature on reactive power management in smart grids enabled by the internet of things has mostly concentrated on optimization methods [21], real-time monitoring, and cybersecurity measures [22]. While some research focuses on cybersecurity and fault detection without doing thorough system-level diagnostics, the majority of studies use static or conventional machine learning models that cannot adapt to changing grid conditions [23]. Also, most of the research focuses on centralized control systems, which have problems with scalability and responding quickly enough in large-scale grids that use DERs [24]. The optimized reactive power management system that has been developed, on the other hand, makes use of kernel debugging to give comprehensive insights into the system as a whole, which in turn allows for the optimization of resource allocation, the detection of anomalies, and the detection of faults in real time. Some operating system kernels come with a built-in debugger called a kernel debugger [25]. This makes it easier for developers to debug and build kernels. Kernel debuggers can take one of two forms: either a command line that can be used directly on the machine being debugged, or a stub that implements low-level operations [26]. Installing a system of sensors all across the power distribution grid to track different metrics in real-time [27]. This may contain essential information such as voltage, current, temperature, and more [28]. By bringing computer capabilities to the edge, data may be processed closer to its source, resulting in reduced latency and faster answers [29]. This is of the utmost importance for applications that rely on time, including fault detection and reaction [30]. The proposed model framework is shown in Figure 2.

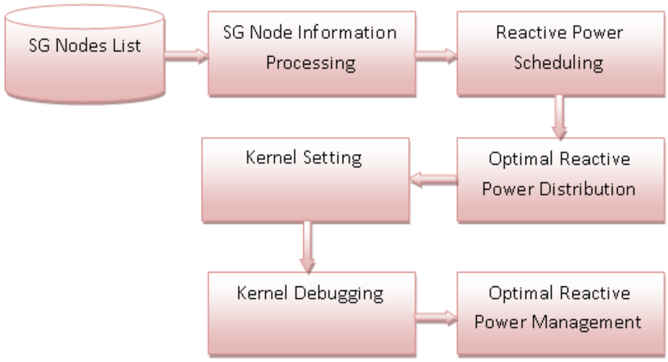

Figure 2. Proposed model framework

A program that is integrated into the kernel and uses data structures provided by the kernel is called a kernel program. When it comes to debugging the kernel, system administrators may also encounter a process hanging or stop operating in power distribution, change in kernel parameters affecting reactive power management and SG crashes or link breaks. This research proposes an ORPM-SG-KDM for managing reactive power efficiently.

Algorithm 1. ORPM-SG-KDM
{**Input:** SG Nodes List {SGNset}
Output: Power Schedule {Pschd}
Step-1: The nodes information is processed and maintained at the network authority. This SG nodes information is helpful for communicating with the other nodes securely. The node information is also used for power distribution to the other nodes and maintaining that information also. The node information processing is performed as (1),

$$Ninfo[M] = \sum_{n=1}^{M} getaddr(n) + \omega(n) + \lambda(n, n+1) + \delta(n) + Th \quad (1)$$

Here node address is used to consider the address of node in smart grid, ω is the model for considering the transmission range of node and λ is the model that considers the adjacent node with minimum distance, δ is the model considering the energy utilization levels. Th is the threshold value initiated to 100.
Step-2: When it comes to running electrical power systems efficiently, one of the biggest concerns is finding the appropriate schedule for reactive power. Optimal control variable settings for reactive power generators to optimize a certain objective function while satisfying all technological restrictions is the goal of this mixed integer and nonlinear problem. When it comes to the efficiency and security of the power system, voltage is a key performance indicator. It is a measure of the power system's reactive power balancing and distribution performance. The reactive power scheduling is performed as (2) and (3),

$$Rpow[M] = \prod_{n=1}^{M} \frac{\gamma(n,n+1)}{M-n} + \lim_{n \to M} \left(min\ (\lambda(n, n+1)) + \frac{\mu(n)}{M} \right)^{T} \quad (2)$$

$$Rpowsched[M] = \sum_{n=1}^{M} \max\big(\omega(n, n+1)\big) + \frac{Rp(\alpha(n)) + \varphi(\mathrm{Ninfo}(n))}{M} \quad (3)$$

Here γ is the model that considers the generated power, μ is the model that considers the nodes to distribute the power in the SG, α is the model that calculates the reactive power Rp maintained at a node n and φ is the model that calculates the total reactive power allocates to a node n and T is the voltage considered
Step-3: Processing of topologies and state estimates are the main components. The topology processing unit converts the network model into a matrix-ready node branch representation by making use of the current state of the switches, which include isolators and breakers.
Reactive power (Q) refers to the amount of energy that can be stored and released by AC circuit components that are inductive and capacitive.

Multiplying the current ($i(t)$) and voltage ($v(t)$) at any given time yields the instantaneous power ($p(t)$) in an alternating current (AC) circuit.

$$v(t) = V_m sin(\omega t) \tag{4}$$

$$i(t) = I_m \sin(\omega t + \theta) \tag{5}$$

Here V_m and I_m are the peak ranges of voltage and current and ω is the angular frequency. Θ is the phase difference between the voltage and the current waveforms.
The instantaneous power is calculated as

$$P(t) = v(t) * i(t) \tag{6}$$

$$p(t) = V_m \sin(\omega t) * I_m \sin(\omega t + \theta) \tag{7}$$

The trigonometry identity of the sines product is obtained as

$$p(t) = \frac{V_m I_m}{2}\cos(\theta) - \frac{V_m I_m}{2}\cos(2\omega t + \theta) \tag{8}$$

The average power is the average value of instantaneous power over once cycle is calculated as (9),

$$P = VI * cos(\theta) \tag{9}$$

The relationship function among *V* and *I* is calculated as (10),

$$P = \sqrt{(v * i)^2 - (v * i * cos(\theta))^2} \tag{10}$$

The reactive power management is performed as (11),

$$P = (v * i) * \sqrt{1 - cos^2(\theta)} \tag{11}$$

$$ORp[M] = \sum_{n=1}^{M} \begin{matrix} \max(\mathrm{P}(\alpha(\mathrm{n}))) & where\ \alpha(\mathrm{n}) > Th \\ \min(\mathrm{P}(\alpha(\mathrm{n}))) & where\ where\ \alpha(\mathrm{n}) < Th \end{matrix} \tag{12}$$

$$ORpdis[M] = \prod_{n=1}^{M} \max\big(ORp(n)\big) - \min\big(ORp(n)\big) + Rpowsched(n, n+1) \begin{cases} ORp(n) < \alpha(\mathrm{M}) \\ ORp(n) > \alpha(\mathrm{M}) \\ null \end{cases} \tag{13}$$

Here Th is the threshold value considered for reactive power generated range.
Step-4: The kernel is an operating system software that typically has full authority over the whole system. The kernel is likewise in charge of avoiding or reducing the severity of process disputes. It is common practice for systems engineers to debug kernel programs they write. A program that is integrated into the kernel and uses data structures provided by the kernel is called a kernel program. The kernel setting and kernel debugging is performed as (14) and (15),

$$KerSet[M] = \sum_{n=1}^{M} \lim_{n \to M} \left(ORpdis(n) + \frac{\alpha\big(\mathrm{ORpdis(n)}\big) + \alpha(\mathrm{OPpdis(n+1)})}{ORp(n)}\right)^T \tag{14}$$

$$KerDebug[M] = \sum_{n=1}^{M} \frac{KerSet(n)}{M} + \max\left(simm(\alpha\big(\mathrm{ORpdis(n, n+1)}\big) + \omega(\mathrm{KerSet(n)})\right) \tag{15}$$

Step-5: There is typically more than one best solution in the search space for optimization issues in the real world because the variables interact in complicated and non-linear ways. The efficiency with which classical algorithms handle optimization problems can vary depending on the nature of the problem at hand. An essential aspect of the operation of the power system is reactive power scheduling and management, a mixed-integer programming problem that is both nonlinear and complex. All of the equality and inequality criteria are satisfied while it optimizes a given objective function. The optimal reactive power management is applied and schedule is generated as (16) and (17),

$$ORPM[M] = \sum_{n=1}^{M} \min\left(simm\left(KerDebug(n, n+1)\right) + \max\left(\omega\left(\mathrm{KerSet(n)}\right) + \max\left(Rpowsched(n)\right)\right)\right) \quad (16)$$

$$Pschd[M] = \sum_{n=1}^{M} ORpdis(n) + \max\left(KerSet(n)\right) + \lambda(n) + \max\left(Rpowsched(n, n+1)\right) \quad (17)$$

}

4. RESULTS

It is critical for power systems to have a systematic way of handling reactive power. Power systems have been divided into three main groups as part of the electrical sector's reform initiatives: generation, transmission, and distribution. An independent system operator oversees each of these entities. The autonomous grid operator is responsible for creating an environment where energy contracts may be executed throughout the transmission infrastructure, and active power is the most traded commodity in the electrical market. Among the many ancillary services needed in a competitive market, providing enough reactive power to maintain grid safety and voltage stability is of utmost importance. The lack of sufficient reactive power in the grid is a major obstacle to the fulfillment of energy contracts since it endangers the grid's operational safety and voltage balance. If the active power market consistently produces the same results, then the reactive power load can be optimally distributed. Generators are provided with ongoing remuneration under this conceptual framework for providing the reactive power necessary to sustain their active energy production activities. This research proposes an ORPM-SG-KDM for managing reactive power efficiently. The proposed model is compared with the traditional voltage variation mitigation using reactive power management of distributed energy resources in a smart distribution system (IBDER) and real-time energy management in smart homes through deep reinforcement learning (RTEMSH-DRL). The proposed model optimized power management is very efficient when contrasted with the traditional methods.

Among the most difficult and intricate issues in the operation of contemporary power systems is the optimal scheduling of reactive power. The advent of liberalization or deregulation in the electricity business, where reactive power is exchanged as an additional service, has recently sparked great scrutiny from scientists and researchers worldwide. In order to minimize system costs while simultaneously minimizing losses, the optimal reactive power scheduling issue must adhere to a number of inequality and equality-based restrictions. Figure 3 represents the reactive power scheduling accuracy levels.

It is critical to specify the particle-specific variable vector in order to handle the appropriate reactive power distribution during operation. There is a grand total of 90 entries for the variable vector of each particle in the SG that is being considered, which includes 39 buses and 12 transformers that include tap changers. A power system's performance indices can be optimized by reactive power distribution optimization by modifying the generator voltage, transformer ratio, and output force of the reactive power compensation device in response to the active power flow that is already known. The optimal reactive power distribution accuracy levels are shown in Figure 4.

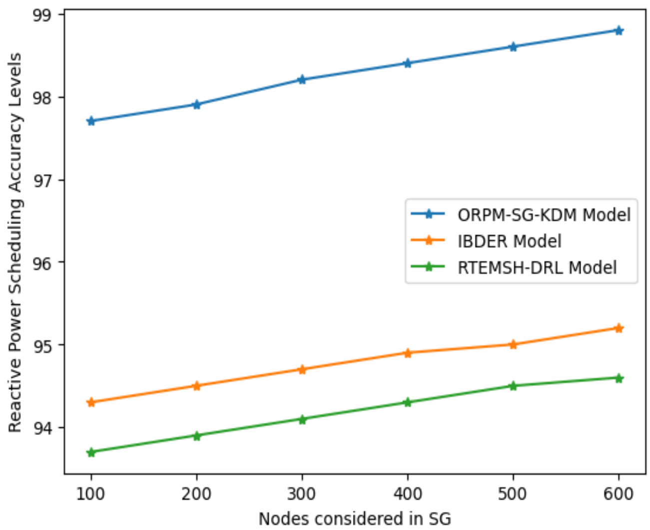

Figure 3. Reactive power scheduling accuracy levels

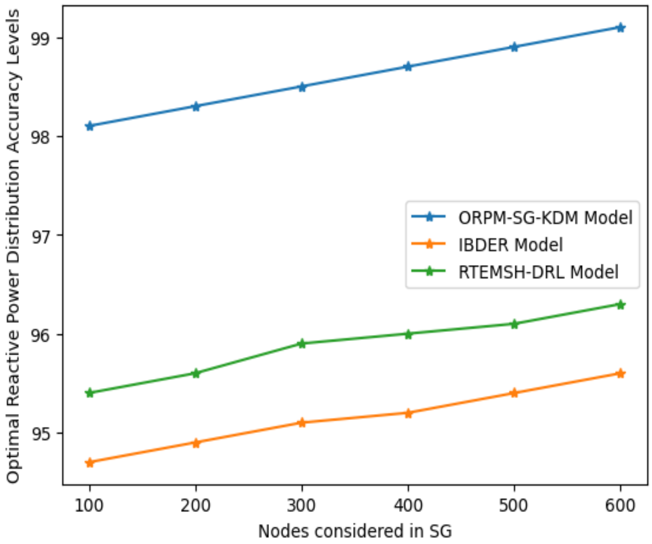

Figure 4. Optimal reactive power distribution accuracy levels

To make debugging and kernel development easier, certain operating system kernels include a debugger called a kernel debugger. Another machine, running a full-blown debugger like GNU Debugger, can send commands to the kernel debugger stub over a serial line or via a network connection, or the debugger can provide a set of commands that can be used immediately on the system being debugged. A kernel debugger can also be a stub that implements low-level operations. The Kernel debugging accuracy levels is represented in Figure 5.

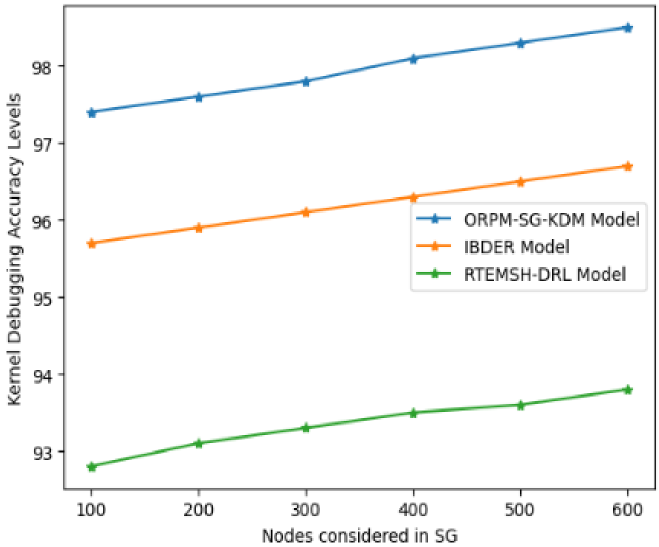

Figure 5. Kernel debugging accuracy levels

Regulating voltages, improving system efficiency, enhancing power transfer capability, achieving cost savings, managing congestion, and facilitating the integration of renewable energy sources are all vital functions of optimal reactive power management. A power system's performance indices can be optimized by reactive power management optimization by modifying the generator voltage, transformer ratio, and output force of the reactive power compensation device in response to the active power flow that is already known. The optimal reactive power management accuracy levels are depicted in Figure 6.

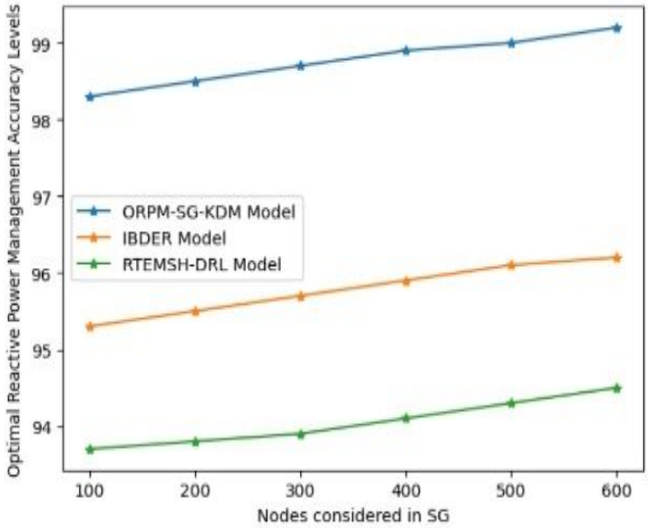

Figure 6. Optimal reactive power management accuracy levels

5. CONCLUSION

To guarantee the efficiency and dependability of the energy supply required to sustain smart cities, it is essential to evaluate energy and power quality indicators in a smart grid that supplies power to smart homes. A collection of inexpensive smart meters with IoT capabilities are used to monitor energy data in this research. The use of smart meters can provide valuable information on the measurement of energy production and consumption. Homeowners and utility companies alike can use this information to better manage energy use, cut down on waste, and adjust generation to meet current demand. This model makes use of the voltage stability margin to guarantee the attainment of maximum active power contracts in the market and to protect operational safety. This model also includes reactive power provision as a service. This research proposes a ORPM-SG-KDM for managing reactive power efficiently. By including additional variables, such as the voltage stability index, into the optimization cost function, the suggested method can be made more effective in the realm of perspective works. As a result, the network's voltage dynamic stability might be enhanced, protecting the weakest buses against voltage collapses. This research achieved 98.5% accuracy in kernel debugging and 99.2% accuracy in optimal reactive power management. Kernel Debugging Accuracy is increased by 1.8% and 3% of reactive power management accuracy is increased. In future, meta heuristic optimization techniques can be applied to the proposed model for better quality of service levels in SG.

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C	:	**C**onceptualization	I	:	**I**nvestigation	Vi	:	**Vi**sualization
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Va	:	**Va**lidation	O	:	Writing -**O**riginal Draft	Fu	:	**Fu**nding acquisition
Fo	:	**Fo**rmal analysis	E	:	Writing - Review &**E**diting			

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, MJR, upon reasonable request.

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